Does convertible arbitrage risk exposure vary through time?

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Abstract

This paper models the returns of the convertible arbitrage hedge fund strategy using a non-linear framework. Investors in the CA strategy have experienced long periods of persistent positive returns accompanied by low volatility, followed by shorter periods of extreme negative returns and high volatility, associated with periods of broad market upheaval. The smooth transition regression (STR) model specified in this study is particularly appropriate for assessing the performance of a strategy of this nature, as it allows for smooth transition between risk regimes. We find that in the alternate regimes the strategy exhibits relatively high (low) exposure to risk factors and alpha is high (low). We suggest that evidence reported in this paper accounts for abnormal returns reported for the strategy in previous studies.

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1. Introduction

From 1997 to mid-2007 hedge funds pursuing the Convertible Arbitrage (CA) strategy generated a Sharpe Ratio above 1.50 and assets under management grew from $5bn to $57bn.[1] At their peak, CA funds accounted for 75% of the market in convertible bonds (Mitchell et al. (2007)). Subsequently, during the financial crisis, CA was the second worst performing hedge fund strategy, losing 35% from September 2007 to December 2008.[2] Since then, despite relative strong post 2008, performance the strategy has generally been shunned by institutional investors with AUM, currently $29.5bn, remaining well below peak values.

In this paper we investigate whether a non-linear model specification improves understanding when modelling CA hedge fund returns. Academic literature on hedge fund performance has generally focused on linearly modelling the relationship between the returns of hedge funds and the asset markets and contingent claims on those assets in which hedge funds operate. Recently, several studies model the returns of these funds using techniques which capture the non-linear relationship between the returns of these strategies and risk factors. We focus on the smooth transition regression (STR) family of models which has the advantage over alternative non-linear regime switching specifications of allowing a smooth transition between different risk regimes when modelling financial data.[3]

Many studies have documented non-linearity in hedge fund returns, see, for example, Liang (1999), Agarwal and Naik (2000), Kat and Brooks (2001), Kat and Lu (2002) and Fung and Hsieh (1997, 2000). One avenue of research has modelled this non-linearity in a linear asset pricing framework using non-Gaussian risk factors. Fung and Hsieh (2001, 2002, 2004) present evidence of hedge fund strategy payoffs sharing characteristics with lookback straddles, and Mitchell and Pulvino (2001) document the returns from a merger arbitrage

[1] Source: Barclayhedge.
[2] HFRI Convertible Arbitrage Index.
[3] In financial markets with many participants operating independently and at different time horizons, movements in asset prices are likely to be smooth.

portfolio exhibiting similar characteristics to a short position in a stock index put option. Using option payoffs as risk factors, Agarwal and Naik (2004) demonstrate the non-linear relationship between hedge fund returns and risk factors. Modelling the returns of CA hedge funds, both Hutchinson and Gallagher (2010) and Agarwal et al. (2011) construct factor portfolios mimicking convertible arbitrage investments.

In addition to the linear factor model literature, several studies utilize models whose functional specification, rather than factor specification, captures these non-linear relationships. Rather than specifying factors with dynamic return distributions, these studies relax the assumption of a linear relationship between risk factors and hedge fund returns. Kat and Miffre (2008) employ a conditional model of hedge fund returns which allows the risk coefficients and alpha to vary. Kazemi and Schneeweis (2003) explicitly address the dynamics in hedge fund trading strategies by specifying conditional models of hedge fund performance. They employ a stochastic discount factor model which has previously been employed in the mutual fund literature. Alternately, Amin and Kat (2003), evaluate hedge funds from a contingent claims perspective, imposing no restrictions on the distribution of fund returns.

STR models were developed by Teräsvirta and Anderson (1992) for modelling non-linearities in the business cycle and offer several advantages over a Hamilton (1989) Markov switching model. STR models incorporate at least two alternate regimes, allowing for a smooth transition from one regime to another. These models have been specified extensively to model economic time series (see, for example, Sarantis (1999), Skalin and Teräsvirta (1999), Ocal and Osborn (2000) and Holmes and Maghrebi (2004)) and stock returns (see, for example, McMillan (2001) , Bradley and Jansen (2004), Bredin and Hyde (2008), Coudert et al. (2011) and Aslanidis and Christiansen (2012)).

In this paper we make two key contributions to the literature on hedge funds. First, we present evidence of a non-linear relationship between CA hedge fund returns and fixed income risk factors. This non-linear relationship is modelled using logistic smooth transition regression (LSTR) models. Second, we provide evidence that the specification of these models reveals new information about the performance of CA fund managers in different market conditions. Eight CA hedge fund series are modelled, including four hedge fund indices and four portfolios made up of individual CA hedge funds.

Our findings are of particular importance to investors in hedge funds. The skill of these managers is more truly reflected when considered in a non-linear framework. When equity markets decline, fixed income risk exposures increase and hedge funds pursuing the strategy outperform a passive investment in the risk factors. Alternately, when equity markets increase, risk exposures fall and the alpha of the strategy is close to zero for all of the series.

Our findings on hedge fund manager skill relate to existing academic studies demonstrating that CA hedge funds generate can significant abnormal returns. In studies of general hedge fund performance, Capocci and Hübner (2004) and Fung and Hsieh (2002) provide some evidence of CA performance. Capocci and Hübner (2004) specify a linear factor model to model the returns of several hedge fund strategies and estimate that CA hedge funds earn an abnormal return of 0.4% per month. Fung and Hsieh (2002) estimate the CA hedge fund index generates alpha of 0.7% per month. Coën and Hübner (2009) develop a higher moment estimation model to improve the accuracy of estimates of abnormal returns and, using this, demonstrate the abnormal return of CA strategies is underestimated using linear models. Focusing exclusively on CA hedge funds Hutchinson and Gallagher (2010) find evidence of individual fund abnormal performance but no abnormal returns in the hedge fund indices. Chan and Chen (2007) provide evidence of consistent under-pricing of new issues while Choi et al. (2010) show that CA funds are the dominant purchasers of these issues and consequently as suppliers of capital to issuers. Agarwal et al. (2011) document positive abnormal returns which they account for with new issue convertible bond under-pricing data.

Several hedge fund trading strategies have been shown to be sensitive to changes in market states, including cross sectional momentum (Cooper et al. (2004); Daniel and Moskowitz (2014)), merger arbitrage (Mitchell and Pulvino (2001)), time series momentum (Hutchinson and O'Brien (2015)) and pairs trading (Bowen and Hutchinson (2015)). By identifying a change in risk exposure in different equity market regimes we demonstrate an appropriate functional model to more fully explain CA risk. Holding a long position in a convertible bond and a corresponding short position in the underlying stock, CA funds are hedged against equity market risk but are left exposed to default and term structure risk. Agarwal and Naik (2004) provide evidence that CA hedge fund indices' returns are positively related to the payoff from a short equity index option, highlighting the non-linearity of their returns.

The remainder of this paper is organised as follows. The next section contains details of the data. Section 3 provides a review of the smooth transition regression models. Section 4 provides details of the estimation results. Section 5 concludes.

2. Data

Our sample of CA hedge funds consists of monthly net-of-fee returns of live and dead funds in the union of the Bloomberg, HFR and Lipper/TASS databases from January 1994 to September 2012.[4] In total the three databases contain 728 funds which are classified as CA. However, this broad sample contains multiple share classes of the same fund and there are significant overlaps across the three databases. Our sample is reduced to 288 unique funds

[4] The database vendors typically do not keep information on funds that died before December 1993 which may lead to survivorship bias. Hence our sample of fund returns begins in January 1994.

after removing funds which report only gross returns and funds which do not report monthly returns. We then remove funds with less than twenty four months of return history leaving a final sample of 254 funds.[5]

To model the convertible arbitrage hedge fund strategy we also specify four indices of CA hedge funds and four portfolios made up of CA hedge funds from our merged sample. The indices specified are the CSFB Tremont CA Index, the HFRI CA Index, the Barclay Group CA Index and the CISDM CA Index. The CSFB Tremont CA Index is an asset weighted index (rebalanced quarterly) of CA hedge funds beginning in 1994, the CISDM CA Index represents the median fund performance, whereas the HFRI and Barclay Group CA Indices are both equally weighted indices of fund performance. The Barclay Group index begins on January 1997 and all other series beginning in January 1994.

The four portfolios are; EQL, an equally weighted portfolio of CA hedge funds; LRG, an equally weighted portfolio made up of the largest funds, ranked by month *t-1* assets under management; MID, an equally weighted portfolio made up of the mid ranking funds, ranked by month *t-1* assets under management and SML, an equally weighted portfolio made up of the smallest funds, ranked by month *t-1* assets under management.

Descriptive statistics of the eight hedge fund series are reported in Table 1 and their cumulative returns are reported in Figure 1. Mean returns range from 5.8% (SML) to 9.1% (MID) and the annualised standard deviations of the series are typically in the range of 5% to 7%, with the exception of SML which is much larger at 13%. All of the hedge fund series, with the exception of SML have a Sharpe ratio greater than 1. Also notable is the large negative skewness and excess kurtosis reported for all series. This is the first evidence that the returns of the CA strategy have non-normal statistical characteristics.

<Insert Table 1 here>

[5] CA has had significant attrition rates, particularly during the 2008 financial crisis. This is very evident in our sample with only 52 unique live funds at the end of the period.

This characteristic of CA is captured quite dramatically in the cumulative returns for the series, reported in Figure 1. The financial crises period from mid-2007 to late 2008 is a period of extremely poor performance for CA with investors losing between 30% and 50% of historical cumulative returns in an extremely short period. It is also quite notable that since the start of 2009 performance has been strong, with all portfolios (except SML) surpassing their previous peaks by early 2010.

<Insert Figure 1 here>

3. Methodology

In this section we discuss the risk factor models and the STR methodology specified in this study to model CA returns.

3.1 Risk Factor Models

There are a range of alternate factor specifications proposed in the literature. In this paper we aim to identify the functional model for estimating these factors that best captures the systematic non-linearity in CA hedge fund returns. The general risk-adjusted hedge fund performance estimation equation is:

$$r_{it} = \hat{\alpha}_i + \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \hat{\varepsilon}_t^i \quad (1)$$

where r_{it} is the net-of-fees excess return on hedge fund *i* at time *t*, $\hat{\alpha}_i$ is the estimated abnormal performance of the hedge fund, $\hat{\beta}_k^i$ is the estimated risk factor loading of hedge fund *i* for risk factor *k*, $F_{k,t}$ is the return of risk factor *k* for month *t* and $\hat{\varepsilon}_t^i$ is the estimated residual. We review the alternate factor specifications proposed in the literature below.

3.1.1 Fung and Hsieh (2004) Model

The Fung and Hsieh (2004) model is designed to capture the risks in a broad portfolio of hedge funds. Fung and Hsieh (2004) specify two equity risk factors; two fixed income risk factors and three option based risk factors. The two equity factors are *SNPRF*, the total return on the Standard & Poor's 500 index, and *SCMLC*, the Size Spread Factor (Russell 2000–S&P 500 monthly total return)[6] while the two bond-oriented risk factors are *BD10RET*, the monthly change in the 10-year treasury constant maturity yield (month end-to-month end), and *BAAMTSY*, a credit spread factor (the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield (month end-to-month end)). Finally, the three option based factors are derived from option prices of futures contracts from three underlying markets, specifically Bond (*PTFSBD*), Currency (*PTFSFX*) and Commodity (*PTFSCOM*).[7]

3.1.2 Agarwal et al. (2011) Model

The Agarwal et al. (2011) model is a variation of the Fung and Hsieh (2004) approach adapted for CA hedge funds. The authors specify two factors to capture both the buy-and-hedge and buy-and-hold return drivers of CA returns.

The buy-and-hedge strategy, which they term the *X* factor, is constructed as a long position in a portfolio of convertible bonds combined with a delta neutral hedged short position in a portfolio of equities. This hedged position is dynamically rebalanced daily. Agarwal et al. (2011) use a custom dataset of convertible bonds and issue weighed equities for their hedged portfolio. In the present study we use a long position in the Merrill Lynch Convertible Securities Index combined with a dynamically hedged short position in the S&P500 future. We use the return series of the Vanguard Convertible Securities mutual fund

[6] This is the most up to date definition of the size factor used by Fung & Hsieh, the original paper defines the factor as (Wilshire Small Cap 1750 - Wilshire Large Cap 750 monthly total return).
[7] Details on the construction of the option based factors are available in Fung W, Hsieh DA The risk in hedge fund strategies: Theory and evidence from trend followers. Review of financial studies. 2001; 14; 313-341. and the data from http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.

(VG) to proxy for the performance of a passive buy-and-hold component of the strategy, as specified in Agarwal et al. (2011).

3.2 Smooth Transition Regression Methodology

Next we review the threshold model methodology focusing on the smooth transition regression (STR) model first proposed by Chan and Tong (1986) and extended by Teräsvirta and Anderson (1992) for modelling non-linearity in the business cycle. STR models are specified in this study for two principle reasons. (1) They incorporate two alternate regimes, corresponding with the theoretical relationship between CA returns and risk factors. One regime where the portfolio is more exposed to risk factors and a second regime where the portfolio is less exposed to risk factors. These two alternate regimes allow us to isolate the true skill of hedge fund managers pursuing CA strategies. (2) They incorporate a smooth transition from one risk regime to another. In financial markets with many participants operating independently and at different time horizons, movements in asset prices and risk weightings are likely to be smooth rather than sharp (see, for example, Merton (1987), Barberis and Thaler (2003) and Mitchell et al. (2007)). In this study we specify the excess return on US Equities (RMRF) as the threshold variable, a proxy for aggregate market risk. The performance of a range of trading strategies and has been shown to be variant to changes in market returns (Cooper et al. (2004), Daniel and Moskowitz (2014) and Bowen and Hutchinson (2015)).

Consider the following nonlinear regression model.

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t \tag{2}$$

Where $\alpha' = (\alpha_0, \dots, \alpha_m)$, $\beta' = (\beta_0, \dots, \beta_m)$, $x_t = (1, x_{1,t}, \dots, x_{m,t})$ and the variable z_t is the transition variable. If $f(z_t)$ is a smooth continuous function, the regression coefficient will change smoothly along with the value of z_t. This type of model is known as a smooth transition regression (STR) model. The two particularly useful forms of the STR model that allow for a varying degree of regression decay are the logistic STR (LSTR) and exponential STR (ESTR) models.

Choosing $f(z_t) = [1 + exp(-\gamma(z_t - c))]^{-1}, \gamma > 0$ yields the logistic STR (LSTR) model where γ is the smoothness parameter (i.e. the slope of the transition function) and c is the threshold. In the limit, as $\gamma \to 0\ or\ \gamma \to \infty$, the LSTR model becomes linear as the value of $f(z_t)$ is constant. For intermediate values of γ, the degree of decay depends upon the value of z_t. As $z_t \to -\infty$, $f(z_t) \to 0$ and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As $z_t \to +\infty$, $f(z_t) \to 1$ and the behaviour of y_t is given by $y_t = (\alpha' + \beta')x_t + e_t$.

Choosing $f(z_t) = 1 - exp(-\gamma(z_t - c)^2), \gamma > 0$ yields the exponential STR (ESTR) model. Again, as $\gamma \to 0\ or\ \gamma \to \infty$, the ESTR model becomes linear as $f(z_t)$ becomes constant. Otherwise the model displays non-linear behaviour. It is important to note that the coefficients for the ESTR model are symmetric around $z_t = c$. As $z_t \to c$, $f(z_t) \to 0$ and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As $(z_t - c) \to \pm\infty$, $f(z_t) \to 1$ and the behaviour of y_t is given by $y_t = (\alpha' + \beta')x_t + e_t$.

STR models are estimated in three stages, following Granger and Terasvirta (1993):

(a) Specification of a linear model.

The initial step requires the specification of the linear model (3).

$$y_t = \alpha + \beta' x_t + \varepsilon_t \tag{3}$$

Where y_t is the excess return on the hedge fund index, and x_t is an n x t matrix of CA risk factors.

(b) Test of linearity

The second step involves testing linearity against STR models using the linear model specified in (a) as the null. To carry out this test the auxiliary regression is estimated:

$$u_t = \beta_0' x_t + \beta_1' x_t z_t + \beta_2' x_t z_t^2 + \beta_3' x_t z_t^3 \tag{4}$$

Where the values of u_t are the residuals of the linear model specified in the first step and z_t is the transition variable. The null hypothesis of linearity is H_0: $\beta_1 = \beta_2 = \beta_3 = 0$.[8]

(c) Selection of LSTR or ESTR

If linearity is rejected the selection between LSTR and ESTR models is based on the following series of nested *F* tests.

$$H_3: \beta_3 = 0 \tag{5}$$

$$H_2: \beta_2 = 0 | \beta_3 = 0 \tag{6}$$

$$H_1: \beta_1 = 0 | \beta_2 = \beta_3 = 0 \tag{7}$$

Accepting H_3 and rejecting H_2 indicates selecting an ESTR model. Accepting both H_3 and H_2 and rejecting H_1 leads to an LSTR model. Granger and Terasvirta (1993) argue that strict application of this sequence of tests may lead to incorrect conclusions. They suggest estimating the *P*-values of the *F*-tests of H_1 to H_3 and selecting the STR model on the basis of the lowest *P*-value will overcome this problem.

We estimate the STR models using non-linear least squares in the RATS programme. RATS specifies the Marquardt variation of Gauss-Newton to solve the non-linear least squares regression.

4. Empirical Results

In this section of the paper we present the empirical results from estimating the STR models for the eight CA series. The remainder of this section is divided into three subsections. Subsection 4.1 presents results from estimation of the linear model; subsection

[8] Equation (5) can also be used to select the transition variable z_t. We conducted this test for each candidate for the transition variable drawing from the matrix of convertible arbitrage risk factors. As it leads to the smallest *P*-value for each of the series, we fail to reject RMRF as the choice of z_t. These results are available from the authors on request.

4.2 presents the linearity test results and, finally, subsection 4.3 presents results from estimating the STR models.

4.1 Linear Model results

The results for the linear factor model are presented in Table 3.

[Insert Table 3 around here]

The table lists the factor coefficients for both the Fung and Hsieh model and the Agarwal et al. specification. Both models perform well for both the CA fund portfolios and indices, with adjusted R^2 values ranging from 38% to 69%. For the Fung and Hsieh model the equity and bond market risk factors exhibit statistical significance, whereas, using the Agarwal et al. models, both X, the delta neutral hedged CA factor, and VG, the long only convertible bond factor, are statistically significant for all the series (with the exception of X for SML).

From a practitioner's perspective the most important coefficient is the intercept, which is a measure of skill by CA hedge fund managers (Jensen (1968)). All of the hedge fund portfolios and hedge fund indices have significantly positive alpha, with the exception of SML, the portfolio of small CA hedge funds, which is insignificantly different from zero for the Fung and Hsieh model and significantly negative for the Agarwal et al. model.

The evidence from the linear model suggests that managers pursuing the CA strategy do generate alpha for their investors, with the exception of managers with relatively limited assets under management. Later we will consider results for the non-linear model to see if these conclusions hold.

4.2 Linearity Tests

The linearity tests for each of the series are displayed in Table 4. For both factor models linearity (H_0) is rejected for all of the hedge fund series. Generally, H_1 and H_2 are rejected for all series, with the exception of CSFB for the Fung and Hsieh model. H_3 is not rejected for three of the series (SML, LRG and CSFB) in the Agarwal et al. model and one of the series (BCLY) for the Fung and Hsieh model.

[Insert Table 4 around here]

Taken together the results of the STR tests suggest that the most appropriate nonlinear model is LSTR. In the next section we report results from estimating the LSTR model for all series using the two alternate factor model specifications.

4.3 Smooth Transition Regression Model

The results of the estimation of the LSTR model are presented in Table 5. Panels A and B show the results for the Fung and Hsieh and the Agarwal et al. risk models respectively. Consistent with theoretical expectations, the estimated parameters of the LSTR model provide evidence of the existence of a non-linear relationship between CA returns and explanatory risk factors; this result is consistent across all eight of the CA return series. We identify two alternate risk regimes for the strategy.[9] Figure 2 shows plots of the transition function again the transition variable (Panel A) and time (Panel B).

[Insert Table 5 around here]

[Insert Figure 2 around here]

[9] For estimation convergence we set c = 0.00 for the Agarwal V, Fung WH, Loon YC, Naik NY Risk and return in convertible arbitrage: Evidence from the convertible bond market. Journal of Empirical Finance. 2011; 18; 175-194. model and c = -0.02 for the Fung W, Hsieh DA Hedge fund benchmarks: A risk-based approach. Financial Analysts Journal. 2004; 60; 65-80. model.

The first regime is defined by the transition variable, z_t, being less than the threshold constant, c, i.e. the current month's excess equity market returns are below the threshold level. This regime is characterised by statistically significant positive abnormal returns (alpha). From Figure 2, Panel B it is clear that this regime coincides with incidences of market stress, with a corresponding decrease in liquidity, such as the 1994 Peso crisis, the 1998 Asian currency crisis, the 2001 Dotcom crash and the 2007-2008 financial crisis.

The second risk regime is defined by the transition variable, z_t, being greater than the threshold constant, c, i.e. the current month's excess equity market returns are above the threshold level and regime is characterised by statistically significant negative abnormal returns (alpha) and is associated with relatively benign financial markets.

The relationship between the CA return series and the risk factors diverges between the two regimes. In the case of the Fung and Hsieh model, the relationship between the return series and the equity size spread, bond yield and credit spread is significantly negative for all series in the high alpha regime; while in the low alpha regime the relationship is positive in all cases and statistically significant in twenty out of twenty four. The magnitude of the relationship is also greater in the high alpha regime in all cases. A similar pattern is seen in the case of the Agarwal et al. model, where the exposure to the risk factors changes sign and increase in magnitude when moving from the low alpha to the high alpha regime.

[Insert Table 6 around here]

In Table 6, we repeat the analysis of Table 5 using the Getmansky et al. (2004) specification to unsmooth hedge fund returns. The results are almost identical to those reported in Table 5.

The presence of the two risk regimes documented in this paper has important implications for investors in CA hedge funds. Though these funds have historically offered high returns with relatively low standard deviation and exposure to market risk factors, this appears due to the generally favourable market conditions. The evidence presented in this paper indicates that in future periods of market stress the strategy will become significantly exposed to fixed income risk factors, but will out-perform a passive investment in these factors.

5. Conclusions

The tests conducted in this paper have rejected a linear relationship between CA hedge fund return series and risk factors. These hedge fund series are classified as logistic smooth transition regression (LSTR) models. The estimated LSTR models provide a satisfactory description of the non-linearity found in CA hedge fund returns and have superior explanatory power relative to linear models. The estimated LSTR model improves efficiency relative to the linear alternative for all the CA return series analyzed.

The estimates of the transition parameter indicate that the speed of transition is relatively slow from one regime to another but the factor loadings become relatively large, and alphas become positive, as current month's excess equity market returns move below the threshold level. Historically the switch into the positive alpha regime coincides with several severe financial crises.

We make two key contributions to the understanding of CA and hedge fund risk and returns in this paper. First, we identify two risk regimes and subsequently identify market conditions where arbitrageurs under-perform.

Previous research has identified only one risk regime for CA. The evidence presented here supports the existence of two alternate risk regimes, a positive alpha regime, with higher fixed income risk when equity returns are below a threshold level, and a negative alpha regime, with lower fixed income risk when excess equity market returns are above a threshold level.

Prior research has also documented the strategy generating either significantly positive alpha or alpha insignificant from zero. Our finding of positive alpha in the higher risk regime is important for investors in CA hedge funds. Convertible arbitrageurs outperform a passive investment in risk factors in relatively volatility financial markets, when arbitrageurs are more exposed to more risk. Perhaps institutional investors should reconsider the asset class.

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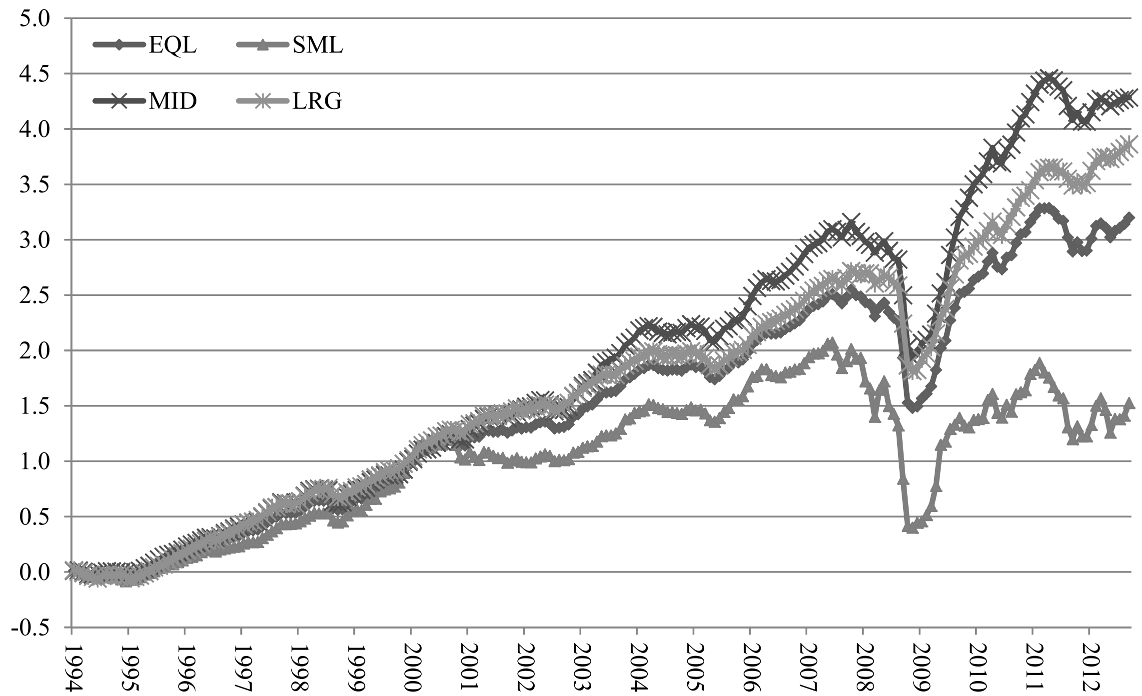
Figure 1
Cumulative returns of the convertible arbitrage series

This figure plots the cumulative returns for each of the convertible arbitrage series over the sample period January 1994 to September 2012. EQL is an equally weighted portfolio of convertible arbitrage hedge funds from the unified database, LRG, MED & SML are equal weighted portfolios of large, medium and small size (assets under management) convertible arbitrage hedge funds from the unified CA database. HFRI is the HFR Convertible Arbitrage Index of hedge funds, CSFB is the CSFB Tremont Convertible Arbitrage Index of hedge funds, BCLY is the Barclay Group Convertible Arbitrage Index of hedge funds and CISDM is the CISDM Convertible Arbitrage Index of hedge funds.

Panel A: Hedge fund portfolios



Panel B: Hedge fund indices

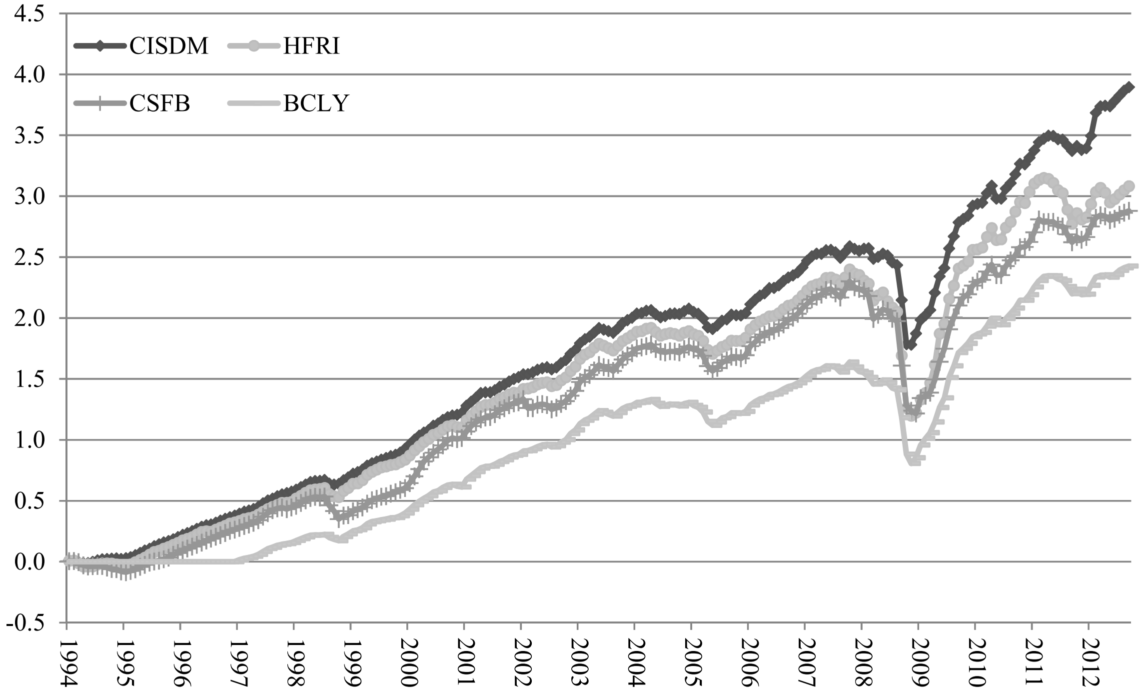
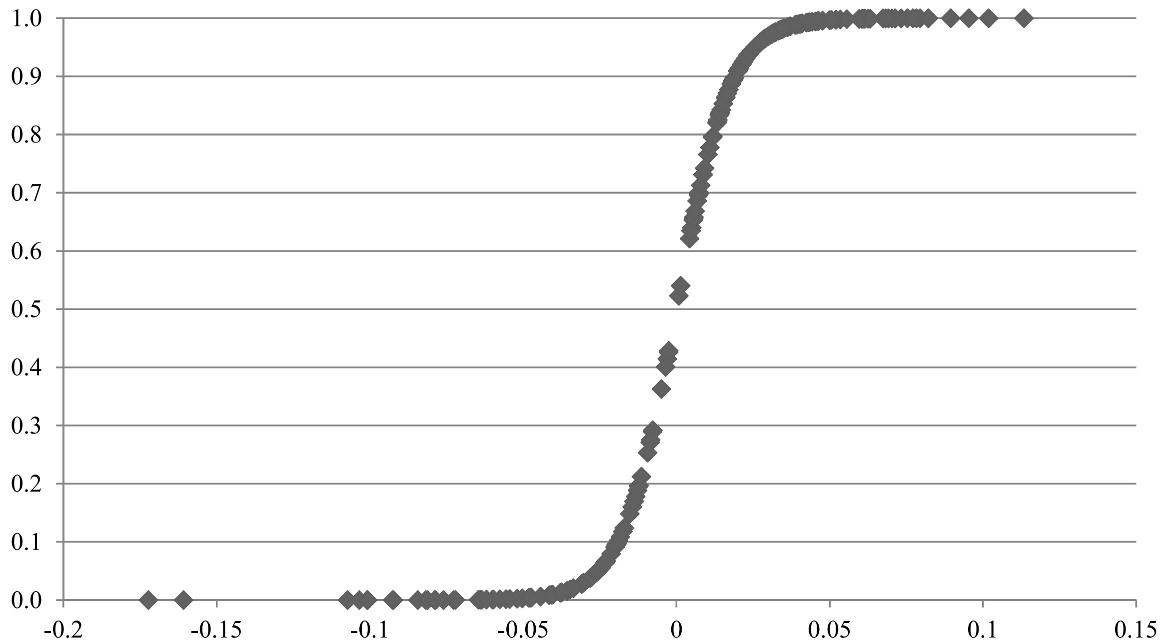


Figure 2
Transition function for the smooth transition regression (LSTR) models

Panel A plots the transition function $f(z_{t41})$ against the transition variable z_t, where z_t is RMRF, the excess return on the aggregate US equity market. The transition function is defined as $f(z_t) = [1 + exp(-\gamma(z_t - c))]^{-1}$. Panel B plots the transition function against time. The sample period is January 1994 to September 2012.

Panel A: Transition function $f(z_t)$ against transition variable



Panel B: Transition function $f(z_t)$ against time

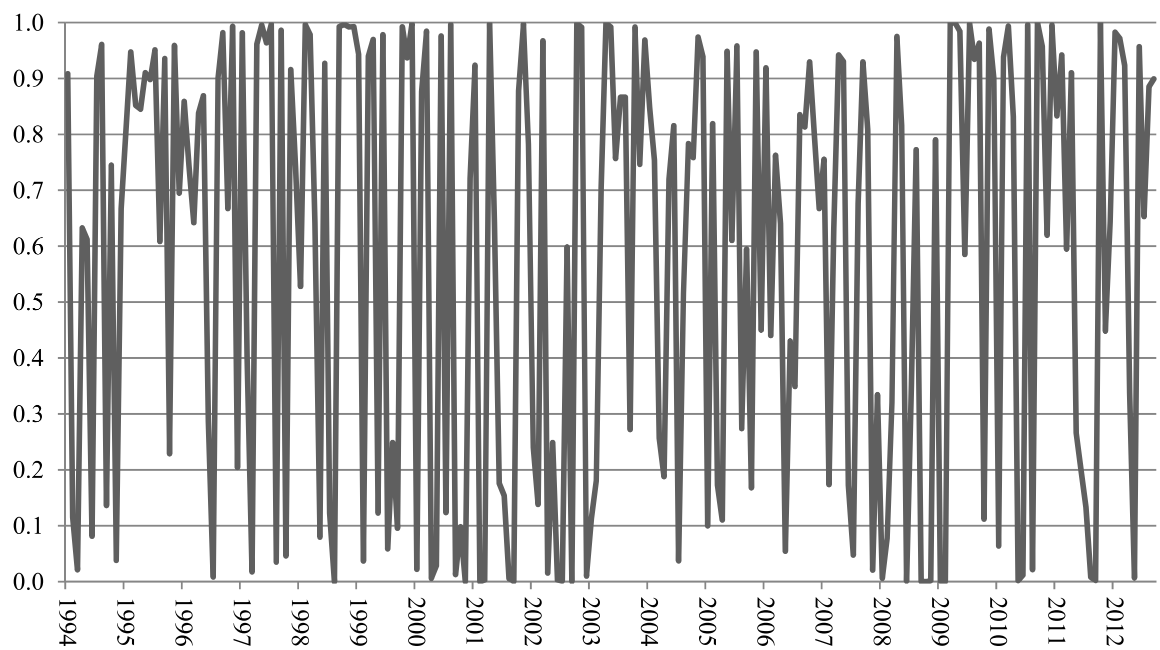


Table 1
Summary statistics of hedge fund returns

The summary statistics are the mean monthly return, μ, standard deviation of monthly returns, σ, the Sharpe Ratio, *SR*, the skewness, *Skew* and the excess kurtosis, *Kurt*. EQL is an equally weighted portfolio of convertible arbitrage hedge funds from the unified database, LRG, MED & SML are equal weighted portfolios of large, medium and small size (assets under management) convertible arbitrage hedge funds from the unified CA database. HFRI is the HFR Convertible Arbitrage Index of hedge funds, CSFB is the CSFB Tremont Convertible Arbitrage Index of hedge funds, BCLY is the Barclay Group Convertible Arbitrage Index of hedge funds and CISDM is the CISDM Convertible Arbitrage Index of hedge funds. The sample period is January 1994 to September 2012.

	μ	σ	SR	Skew	Kurt
Panel A: Hedge fund portfolios					
EQL	7.91	6.76	1.17	-2.46	19.58
SML	5.83	13.05	0.45	-1.28	17.11
MID	9.14	6.69	1.37	-2.19	17.50
LRG	8.64	5.82	1.48	-2.73	21.01
Panel B: Hedge fund indices					
HFRI	7.80	7.23	1.08	-2.80	26.87
CSFB Tremont	7.50	6.87	1.09	-2.68	19.01
Barclayhedge	8.07	6.71	1.20	-2.69	22.47
CISDM	8.64	5.09	1.70	-3.45	29.42

Table 2
Summary statistics and correlation matrix of factors used to analyze hedge fund returns

The summary statistics are the mean monthly return, μ, standard deviation of monthly returns, σ, the Sharpe Ratio, *SR*, the skewness, *Skew* and the excess kurtosis, *Kurt*. SNPRF is the excess return on the S&P 500, SCMLC is the return on small capitalisation minus the return on large capitalisation stocks. BD10RET is the excess return on the 10 year US T-Bond. BAAMTSY is the return on BAA rated bonds minus the return on the 10 Year Bond. PTFSBD, PTFSFX and PTFSCOM are the return on trend following factors for Bonds, FX and Commodities. VG is the excess return on the Vanguard convertible bond mutual fund. X is the return on the delta neutral hedge portfolio of convertible bonds. RMRF is the excess return on US equities. The sample period is January 1994 to September 2012.

	μ	σ	SR	Skew	Kurt
Panel A: Fung and Hsieh factors					
SNPRF	6.17	15.52	0.40	-0.64	3.91
SCMLC	-0.50	11.79	-0.04	-0.29	7.82
BD10RET	-3.66	24.67	-0.15	0.17	5.68
BAAMTSY	1.65	19.81	0.08	-0.22	6.71
PTFSBD	-15.54	53.55	-0.29	1.40	5.53
PTFSFX	-6.38	68.11	-0.09	1.35	5.47
PTFSCOM	-5.46	47.43	-0.12	1.14	5.12
Panel B: Agarwal et al. factors					
VG	5.03	13.01	0.39	-0.94	6.85
X	1.53	9.31	0.16	-0.53	6.31
Panel C: Fama and French Market factor					
RMRF	6.27	15.97	0.39	-0.69	3.94

Panel D: Correlation matrix

	SNPRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	VG	X	RMRF
SNPRF	1.00									
SCMLC	-0.07	1.00								
BD10RET	0.22	-0.17	1.00							
BAAMTSY	-0.38	0.20	-0.89	1.00						
PTFSBD	-0.25	0.12	-0.31	0.34	1.00					
PTFSFX	-0.21	0.02	-0.17	0.26	0.26	1.00				
PTFSCOM	-0.17	0.06	-0.16	0.22	0.21	0.37	1.00			
VG	0.83	-0.38	0.21	-0.44	-0.24	-0.20	-0.17	1.00		
X	0.28	-0.48	0.03	-0.19	-0.13	-0.09	-0.14	0.59	1.00	
RMRF	0.99	-0.21	0.24	-0.40	-0.26	-0.21	-0.17	0.89	0.36	1.00

Table 3
Linear model

This table reports the OLS estimation of the linear models. Coefficients in bold are significant at the 5% level. Panel A reports results for the Fung and Hsieh model. Panel B reports results for the Agarwal et al model. EQL is an equally weighted portfolio of convertible arbitrage hedge funds from the unified database, LRG, MED & SML are equal weighted portfolios of large, medium and small size (assets under management) convertible arbitrage hedge funds from the unified CA database. HFRI is the HFR Convertible Arbitrage Index of hedge funds, CSFB is the CSFB Tremont Convertible Arbitrage Index of hedge funds, BCLY is the Barclay Group Convertible Arbitrage Index of hedge funds and CISDM is the CISDM Convertible Arbitrage Index of hedge funds. The sample period is January 1994 to September 2012.

Panel A: Fung and Hsieh model

	α	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	$\beta_{BAAMTSY}$	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	$\bar{R}^2$
EQL	**0.29**	**0.16**	**-0.08**	**-0.24**	**-0.38**	-0.01	0.00	0.00	67%
SML	0.04	**0.30**	**-0.12**	**-0.39**	**-0.70**	0.00	0.00	-0.01	61%
MED	**0.39**	**0.16**	**-0.11**	**-0.23**	**-0.37**	-0.01	0.00	0.00	67%
LRG	**0.38**	**0.11**	-0.04	**-0.22**	**-0.32**	-0.01	-0.01	0.00	53%
HFRI	**0.31**	**0.09**	-0.03	**-0.30**	**-0.48**	-0.01	0.00	-0.01	57%
CSFB	**0.31**	0.03	-0.03	**-0.28**	**-0.44**	-0.01	0.00	-0.01	46%
BCLY	**0.38**	**0.05**	-0.03	**-0.29**	**-0.43**	-0.01	0.00	-0.01	55%
CISDM	**0.41**	**0.06**	-0.03	**-0.23**	**-0.33**	0.00	0.00	-0.01	54%

Panel B: Agarwal et al model

	α	β_X	β_{VG}	$\bar{R}^2$
EQL	**0.23**	**0.39**	**0.10**	69%
SML	**-0.09**	0.76	**0.03**	58%
MED	**0.34**	**0.38**	**0.09**	67%
LRG	**0.34**	**0.27**	**0.13**	56%
HFRI	**0.25**	**0.32**	**0.13**	48%
CSFB	**0.25**	**0.24**	**0.18**	38%
BCLY	**0.31**	**0.25**	**0.17**	47%
CISDM	**0.36**	**0.22**	**0.11**	48%

Table 4
Linearity and STR tests
This table presents results from a sequence of *F*-tests carried out for each of the convertible arbitrage series following estimation of the following auxiliary regression,

$$u_t = \beta_0 z_t + \beta_1 z_t x_t + \beta_2 z_t x_t^2 + \beta_3 z_t x_t^3$$

In Panel A (Panel B) for each convertible arbitrage series u_t are the residuals from estimating the Fung and Hsieh (Agarwal et al.) linear model, z_t is RMRF, the excess equity market return and x_t is an n x t matrix of risk factors, where n is the number of factors in the Fung and Hsieh (Agarwal et al.) model. The null hypothesis of linearity is H_0: $\beta_1 = \beta_2 = \beta_3 = 0$. The selection between LSTR and ESTR models is based on the following series of nested *F*-tests.

$$H_3: \beta_3 = 0$$
$$H_2: \beta_2 = 0 | \beta_3 = 0$$
$$H_1 \ \beta_1 = 0 | \beta_2 = \beta_3 = 0$$

P-Values in bold are significant at the 5% level.

	EQL	SML	MID	LRG	HFRI	CSFB	BCLY	CISDM
Panel A: Fung and Hsieh model								
H_0	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	**0.00**
H_3	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**	**0.00**	0.11	**0.00**
H_2	**0.00**	**0.01**	**0.00**	**0.04**	**0.05**	**0.02**	0.06	**0.01**
H_1	**0.00**	**0.03**	**0.02**	**0.02**	**0.00**	0.19	0.10	**0.00**
Panel B: Agarwal et al model								
H_0	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
H_3	0.06	0.25	0.06	0.12	**0.04**	0.25	0.05	**0.00**
H_2	**0.00**	0.07	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
H_1	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

Table 5
Smooth transition regression (STR) model

This table reports the NLLS estimation of the logistic smooth transition regression models for each of the convertible arbitrage series. Coefficients in bold are significant at the 5% level. Panel A reports results for the Fung and Hsieh model. Panel B reports results for the Agarwal et al model. EQL is an equally weighted portfolio of convertible arbitrage hedge funds from the unified database, LRG, MED & SML are equal weighted portfolios of large, medium and small size (assets under management) convertible arbitrage hedge funds from the unified CA database. HFRI is the HFR Convertible Arbitrage Index of hedge funds, CSFB is the CSFB Tremont Convertible Arbitrage Index of hedge funds, BCLY is the Barclay Group Convertible Arbitrage Index of hedge funds and CISDM is the CISDM Convertible Arbitrage Index of hedge funds. The sample period is January 1994 to September 2012.

Panel A: Fung and Hsieh model

	$z_t < c$								$z_t > c$										
	α	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	$\beta_{BAAMTSY}$	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	a	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	$\beta_{BAAMTSY}$	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	c	γ	$\bar{R}^2$
EQL	**0.91**	**0.18**	**-0.16**	**-0.35**	**-0.52**	0.00	0.00	0.00	**-0.92**	0.07	**0.10**	**0.21**	**0.26**	-0.01	0.00	0.01	-0.02	**115.3**	71%
SML	0.30	**0.24**	**-0.26**	**-0.62**	**-0.91**	0.00	0.00	-0.01	-0.61	0.19	0.19	**0.38**	**0.39**	-0.01	0.01	0.02	-0.02	111.3	63%
MED	**1.40**	**0.24**	**-0.17**	**-0.31**	**-0.47**	-0.01	0.00	0.00	**-1.39**	0.03	0.07	**0.15**	**0.21**	0.00	0.00	0.01	-0.02	**81.8**	70%
LRG	**0.92**	**0.12**	**-0.10**	**-0.35**	**-0.49**	-0.01	-0.01	0.00	-0.81	0.08	0.07	**0.24**	**0.31**	0.00	0.00	0.00	-0.02	**100.7**	58%
HFRI	**1.34**	**0.14**	**-0.14**	**-0.44**	**-0.66**	-0.01	0.00	0.00	**-1.49**	0.09	**0.13**	**0.26**	**0.34**	0.00	0.00	0.00	-0.02	**92.7**	62%
CSFB	**1.60**	**0.14**	**-0.13**	**-0.37**	**-0.57**	-0.01	0.00	-0.01	**-1.75**	0.01	**0.13**	**0.18**	**0.26**	0.00	-0.01	0.02	-0.02	87.3	50%
BCLY	**1.50**	0.09	**-0.14**	**-0.38**	**-0.61**	0.00	0.00	0.01	**-1.72**	**0.12**	0.13	**0.19**	**0.33**	-0.01	0.00	-0.01	-0.02	64.8	61%
CISDM	**1.30**	0.10	**-0.09**	**-0.35**	**-0.50**	0.00	0.00	0.00	**-1.35**	0.07	0.06	**0.24**	**0.31**	0.00	0.00	-0.01	-0.02	62.2	60%

Panel B: Agarwal et al model

	$z_t < c$			$z_t > c$					
	α	β_X	β_{VG}	α	β_X	β_{VG}	c	γ	$\bar{R}^2$
EQL	**0.92**	**0.52**	**0.12**	**-0.93**	-0.09	-0.09	0.00	262.4	72%
SML	**0.93**	**0.95**	0.05	**-1.46**	-0.11	-0.11	0.00	248.2	60%
MED	**1.02**	**0.51**	**0.11**	**-0.94**	-0.09	-0.08	0.00	179.6	69%
LRG	**1.00**	**0.41**	**0.15**	**-0.82**	**-0.12**	-0.07	0.00	329.1	59%
HFRI	**2.48**	**0.60**	**0.19**	**-4.10**	-0.09	-0.30	0.00	**25.2**	54%
CSFB	**3.45**	**0.61**	0.19	**-5.97**	-0.18	-0.25	0.00	**19.6**	48%
BCLY	**3.16**	**0.64**	0.10	**-4.20**	**-0.19**	-0.11	0.00	**34.1**	57%
CISDM	**2.54**	**0.50**	0.11	**-3.18**	**-0.14**	-0.13	0.00	**34.4**	58%

Table 6
Smooth transition regression (STR) model – Unsmoothed Series

This table reports the NLLS estimation of the logistic smooth transition regression models for each of the unsmoothed convertible arbitrage series. Returns are unsmooth using the Getmansky et al. (2004) methodology. Coefficients in bold are significant at the 5% level. Panel A reports results for the Fung and Hsieh model. Panel B reports results for the Agarwal et al. model. The sample period is January 1994 to September 2012.

Panel A: Fung and Hsieh model

	$z_t < c$								$z_t > c$										
	α	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	$\beta_{BAAMTSY}$	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	α	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	$\beta_{BAAMTSY}$	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	c	γ	$\bar{R}^2$
EQL	**0.96**	**0.25**	**-0.11**	**-0.43**	**-0.56**	-0.01	-0.01	-0.02	**-1.26**	**0.15**	-0.03	**0.28**	**0.28**	0.00	0.01	**0.04**	-0.02	**77.0**	67%
SML	-1.07	-0.51	-0.07	**-1.17**	**-1.13**	-0.04	-0.03	-0.12	1.73	0.69	-0.20	**1.38**	0.82	0.05	0.06	0.21	-0.02	17.7	53%
MED	**1.64**	**0.35**	**-0.12**	**-0.36**	**-0.49**	-0.01	-0.01	-0.02	**-1.93**	0.07	-0.08	**0.19**	**0.22**	0.01	0.01	0.03	-0.02	**69.6**	71%
LRG	0.81	**0.16**	-0.05	**-0.41**	**-0.51**	-0.01	-0.02	-0.02	-0.85	**0.14**	-0.04	**0.27**	**0.29**	0.00	0.01	0.02	-0.02	**93.9**	52%
HFRI	**1.30**	**0.16**	-0.09	**-0.51**	**-0.70**	-0.01	-0.01	-0.02	**-1.64**	**0.16**	0.04	**0.31**	**0.36**	0.00	0.01	0.03	-0.02	**100.8**	56%
CSFB	**1.78**	0.20	-0.03	**-0.43**	**-0.60**	-0.02	0.00	**-0.05**	**-2.27**	0.08	-0.04	**0.22**	0.21	0.01	-0.01	**0.07**	-0.02	**76.8**	37%
BCLY	**1.22**	0.11	-0.08	**-0.43**	**-0.63**	-0.01	-0.01	-0.01	-1.40	**0.14**	0.02	**0.20**	**0.31**	0.00	0.01	0.01	-0.02	**95.6**	57%
CISDM	**1.23**	**0.11**	-0.06	**-0.37**	**-0.50**	0.00	-0.01	-0.01	**-1.30**	**0.09**	0.01	**0.25**	**0.30**	0.00	0.01	0.01	-0.02	**72.8**	58%

Panel B: Agarwal et al model

	$z_t < c$			$z_t > c$					
	α	β_X	β_{VG}	α	β_X	β_{VG}	c	γ	$\bar{R}^2$
EQL	**1.54**	**0.71**	0.12	**-1.81**	-0.09	-0.12	0.00	**64.4**	71%
SML	**1.67**	**1.38**	-0.14	**-2.36**	-0.21	0.07	0.00	115.4	52%
MED	**1.66**	**0.71**	0.10	**-1.85**	-0.11	-0.09	0.00	**52.8**	73%
LRG	**1.66**	**0.54**	**0.25**	**-1.85**	-0.09	-0.19	0.00	**46.4**	58%
HFRI	**2.61**	**0.70**	**0.26**	**-3.31**	-0.11	**-0.32**	0.00	**51.2**	55%
CSFB	**3.13**	**0.71**	**0.34**	**-4.10**	-0.13	**-0.36**	0.00	**47.3**	43%
BCLY	**3.32**	**0.71**	0.15	**-4.51**	-0.16	-0.16	0.00	**34.9**	60%
CISDM	**2.46**	**0.51**	0.14	**-3.06**	-0.10	-0.17	0.00	**37.7**	59%